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An evaluation of mouse and keyboard interaction indicators towards non-intrusive and low cost affective modeling in an educational context

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Abstract

In this paper we propose a series of indicators, which derive from user's interactions with mouse and keyboard. The goal is to evaluate their use in identifying affective states and behavior changes in an e-learning platform by means of non-intrusive and low cost methods. The approach we have followed study user's interactions regardless of the task being performed and its presentation, aiming at finding a solution applicable in any domain. In particular, mouse movements and clicks, as well as keystrokes were recorded during a math problem solving activity where users involved in the experiment had not only to score their degree of valence (i.e., pleasure versus displeasure) and arousal (i.e., high activation versus low activation) of their affective states after each problem by using the Self-Assessment-Manikin scale, but also type a description of their own feelings. By using that affective labeling, we evaluated the information provided by these different indicators processed from the original user's interactions logs. In total, we computed 42 keyboard indicators and 96 mouse indicators.

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Keywords: Affective Computing; Affective States; User Modeling; Human-Computer Interaction; Keyboard; Mouse.

1. Introduction

Nowadays there is growing interest in Computer Science research focused on users' interactions in terms of the emotional impact that can be brought up when in that interaction the human feelings are considered. When he affective dimension of that human-computer interaction is taken into account, the machine should manage

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the emotional aspect of that interaction [1]. In order to offer an adaptive experience dealing with the emotion of their user, computers should be able to detect the affective state of the user according to a given emotional model, process it and adapt those features that are intended to interact with the user's feelings and her current state. This emotional model could consider its influence in human understanding-related characteristics such as attention, memory and aesthetics, even add a touch of emotion in intelligent decision making in computers [2].

Bearing the aforementioned detection problem in mind, in this work we present a combination of keyboard and mouse interaction features (due to their non-intrusive and low cost nature) that can be processed to compute affective information from learners' interactions in a course. We evaluate their use in an educational context and discuss the information gain that they can provide to a multimodal approach for affective states detection, where we look for the data source combination that is most adequate in terms of three evaluation criteria: effectiveness, intrusiveness and price.

The paper is structured as follows. In section 2 we describe some related works that motivate the presented work. In section 3 we present the context of this research, stating its final goals and purposes. In section 4 we explain the work carried out to obtain the proposed feature set from interaction data with keyboard and mouse, including all the stages from the experiment design to the data preparation. In section 5, we report the results obtained. In section 6 we analyze and discuss the obtained data and comment the results and correlations obtained. Finally, in section 7, we conclude and outline future work.

2. Related work

Affective Computing is of relevance in educational contexts since emotions can play an important role in the learning process (e.g., a strong link can be found between affective states and some important features involved in the learning process such as motivation) [3]. Being able to handle the affective dimension of the learning process can result in higher learning effectiveness [4]. Bearing that in mind, the first stage in this research line is to achieve automatic affective states detection.

A review of the literature shows the use of different devices for affective states detection during learning. Most commonly used devices are sensors able to get physiological measures (e.g., heart rate, skin conductance, respiratory frequency, electromyography signals, etc.) [5], which need an expert knowledge on how to get information from the data they offer and are usually expensive and intrusive [6]. Other approaches consider the postural behavior to get information from an affective experience (e.g., using information of the way the learner sits and rests her back against the chair [7], or the pressure of the mouse clicks [8]). This is usually a non–intrusive approach, but relies on special (and expensive) devices created on purpose for the experiments. Another common approach is the use of artificial vision with recordings of the learner's face [9]. Specific measures recorded with eye trackers (such as the pupil dilatation) can help to detect different affective states [10] as well as to monitor the learning process [11].

Another method, neither expensive nor intrusive is to use the most-common existing devices to interact with computers (i.e., the keyboard and mouse) in order to obtain affective indicators. The interaction with these devices has been deeply studied in the last years from many viewpoints, such as interface design [12] or user experience [13]. In particular, there is vast research in the field of biometry. Here, the interaction with keyboard and mouse is modeled in order to detect unique features that can identify a user. In mouse biometric studies, all possible features that can be obtained from mouse interactions are considered, including time between the mouse buttons events [14] and the analysis of the movements performed (coordinates, distance, path, etc.) [15]. In keyboard biometric studies, most works focus on studying short text input (corresponding to passwords) to enrich security systems. Here, a reduced number of keys are considered, mainly in terms of numeric keyboards [16]. Most commonly extracted features used with these purposes are keystroke time, keystroke interval, digraphs, trigraphs, key pressure, errors, text length and text difficulty [17]. When processing large-text inputs [18] additional features such as key press durations, transition times between most common letter pairs, spacebar presses and the keystroke input rate as features are also used [19].

Both keyboard and mouse are also being used on affect detection. Although there are not so many studies as in biometry, several related works in this field can be reported. In particular, regarding mouse interactions, in [20] the mouse movement rate is related to arousal to detect the student's mood. In [21], a series of interaction features are proposed to detect the affective state of a student who attends to an online lesson. The features proposed are generated from the average speed, inactivity, speed and orientation of the mouse movements. In [22], authors propose the use of a biometric mouse to get different indicators, such as mouse speed, acceleration, hand shaking, click coordinates and scrolling. That biometric mouse can also provide temperature, humidity and pressing intensity of the student.

When using keyboard as data source for affect detection, more studies arise. In [23] the features used to perform affective states predictions and discriminate boredom, engagement and neutral states are divided into four categories: relative timing (session and essay timings), keystroke verbosity (number of keys and backspaces), keystroke timing (latency measures) and pausing behaviors. In turn, eight features are extracted in [24] (and are also used in [25]): typing speed, four statistics from the number of typed characters for a 5-second interval, total time taken for typing, number of backspaces and idle times to detect the state of the user from a given list of affective states. In [26] authors choose an approach based on processing combinations of 2 and 3 keystrokes (i.e., digraphs and trigraphs) to extract indicators (e.g., durations and number of events).

Some studies have jointly considered keyboard and mouse interactions to extract affective information from the learner. In [27] authors group the interactions every 10 minutes to process the total number of events registered, such as average time between events, total windows switched, number of backspace and delete key events, alphabetical and numeric key events, number of mouse clicks and number of all other keys. The main focus is on keyboard and mouse click processing, but does not take into account the mouse movements or the distances between clicks. In [28] author compute 64 parameters including mouse clicks, single mouse clicks, distances, speed, clicks times, pauses in the mouse movement, acceleration, angle and direction of the mouse movements, number and length of the keystrokes, etc. but no indicators from keystroke combinations are used. The combined approach is also proposed in [29] but no details of the methodology used are given there.

With the advent of new devices and new ways of interaction, researches are also working on affective states detection using new features and enhanced possibilities, from touch screens [30] to sensors providing environmental data (weather, lighting or location) or behavioral data (device shakes, inclination, etc.) [31].

Based on the interaction features detected in the literature, we propose the unified use of the three different kinds of indicators found: 1) single keystroke features, 2) combined keystroke features and 3) mouse indicators. The goal is to detect users' affective states from their keyboard and mouse interaction features, which is aimed to enrich the multimodal approach we are following for automatic emotions detection [32]. In this approach, we consider additional data sources, such as physiological signals and facial expressions. Our final goal is to identify the most appropriate emotional data sources for computing relevant affective states during the learning process, taking into account aforementioned three criteria: effectiveness, intrusion level and cost.

3. Features proposal

The approach we have followed focused on identifying user's affective states from their keyboard and mouse interactions patterns regardless of the task being performed and its presentation, looking for a solution applicable in any domain. To this end we have followed a thorough state of the art review focused on identifying key features that can be captured from mouse and keyboard interactions. Collected features found in the literature have been extended with others proposed in this work, which were used in an experiment designed to capture participants' emotional perceptions while carrying out mathematical tasks. In particular, students used keyboard and mouse as their basic interaction features. From their analysis we evaluated the correlation between an extended set of keyboard and mouse usage indicators with the emotional reporting of the users associated to the learning tasks carried out. For this, we used a standardize questionnaire, namely, the Self-Assessment Manikin (SAM) [33]), which allows the user to rate her valence (i.e., pleasantness of the emotion) and arousal (i.e., strength of the emotion) in a numerical scale. The indicators used can be divided into three categories: 1) Individual keystroke indicators, 2) Digraphs and trigraphs indicators and 3) Mouse indicators. In total, we computed 42 keyboard indicators and 96 mouse indicators.

Most of the individual keystroke indicators used in our approach were considered in many of the works presented in Section 2 [23, 24]. They were extracted from the logged keystrokes without performing any event combination. These indicators encompass: number of key press events, average time between key press events, average time per stroke (defined as the press of a key and its release), number of times a given key has been pressed (backspace, navigation arrows, delete, tab) or a set of keys has been pressed (alphabetical characters).

The digraphs and trigrahps indicators were computed as proposed in [26]. They generated characteristics obtained from combinations of two and three keystrokes. Computed indicators include measures such as time between down keys, duration of each key event, time between a key up and the following key down, the duration of the digraph/trigraph and the number of events in the key events combination.

Regarding mouse indicators, they are generated from the clicks, cursor movements and scroll movements performed by the participant. Generated indicators comprise: number of button presses (left, right and both), overall distance, distance the cursor has been moved (covered distance) between two button press events, between a button press and the following button release event, between two button release events and between a button release and the following button press events, the Euclidean distance in the previous described cases, the difference between the covered and the Euclidean distance between the events described before and times elapsed between the mentioned events.

4. Experiment

In this section we report the experiment carried out. First, we comment on the experimental design. Next, we describe the data acquisition process. After that, we describe how the data processing was carried out.

4.1. Experimental design

As described in [34], during the Science Week event, which takes place in Madrid on a yearly basis, our research group carried out an experiment for individual Math problem solving involving 75 participants (including 3 participants with accessibility requirements, two of them using Jaws as screen reader, and thus, the keyboard not only for typing but also for browsing). The experiment was structured in two different parts. The first part was set out to check the physiological values registered when intense emotions are displayed to the participants, so they had to answer some tricky and awkward personal questions and evaluate the valence and arousal dimension of their emotions (using the SAM scale) while watching eight images (which progressively featured increasing emotional intensity) collected from the International Affective Picture System (IAPS) [35]. In order to get the baseline for the physiological measures, participants were asked to relax for two minutes before and after the experiment.

The second part of the experiment consisted of three educational tasks, namely, two groups of math problems and a group of logical series. The second group of math problems had a high difficulty and a strict time limit (offering less time than the needed for solving all problems included in the given group), which aims to elicit a stress state. After each problem, participants had to score their affective state with the SAM scale, and after each group of problems or logical series, participants were asked to type their emotions in their own words. During the interaction, other data sources were used. Several physiological signals were captured for further analysis (i.e. heart rate, respiratory frequency, skin conductance and skin temperature) using a J&J

Engineering I-330-C2 system. Moreover, the participant's desktop was recorded with the CamStudio software, and a webcam and a Kinect device were used to register movements and gestures from the participant's face.

In the rest of this paper, we comment only on the mouse and keyboard interactions as source to produce non-intrusive indicators that deal with affective information. In parallel, in other works we are considering the combination of these indicators with other emotional sources (e.g., physiological, facial, etc.). In particular, in [32] two different approaches were explored: sentiment mining for predicting user's emotion from the text typed (in in terms of their emotional report) and prediction of the SAM valence values given by learners after each problem throughout the experiment. There we considered personality traits questionnaires scores, text mining scores, keyboard interactions (at that time, only 16 indicators were computed) and physiological data. In turn, in [36] we proposed and applied an annotation methodology to tag affective-related information from video recordings of facial expressions and body movements in order to train data mining algorithms from where to automatically identify changes in the learners' affective states when dealing with cognitive tasks.

4.2. Data acquisition

To collect all the mouse and keyboard interactions in real time, an invisible mouse tracker and key logger were developed in Java using the kSquared.de library. Since this library does not capture the scroll triggered events, the first version of the mouse tracker did not either. However, we have developed a second version of the mouse tracker, which includes this feature and is to be used in forthcoming experiments. The information captured was saved every 5 seconds in one csv file for keyboard interactions and another csv file for mouse interactions and consists of the following parameters:

- Regarding the keyboard interactions: time (hours, minutes, seconds and milliseconds), event (press or release) and ASCII code and representation for each event registered.
- Regarding the mouse interactions: time (hours, minutes, seconds and milliseconds), event (movement, left or right button pressed or released) and coordinates where the event was registered (in pixels).

4.3. Data processing

The first step was to split the mouse and keystroke logs into the experiment tasks. To this, as it is described in [36], the desktop recordings of the participants were visualized by a psycho-educational expert who focused on adding emotional labels to the data and annotate the transition points between tasks (i.e., start and end time of each task), which were used for splitting the logs (containing 470473 mouse and 54062 keyboard events registered). Due to complexity and time involved in this labeling process, up to the moment data from 17 participants has been annotated and thus, processed. After that, a Java application was used to process the csv files containing the mouse and keyboard indicators for each of the experiment tasks, resulting 51 labeled interaction fragments per data source. Table 1 shows some information from the emotional scores reported by the participants in average per task.

Table 1. Statistics about the SAM scores given by participants in average by task.

	Valence	Arousal
Minimum	1	2
Maximum	8.65	9
Mean	4,487	4,387
Standard deviation	1,768	1,705

Regarding the design of the experience, some facts were taken into account when processing the data. Due to the absence of keyboard interactions in the problem solving tasks, and the intense use of them when writing the emotional reports, the dataset was divided into two partial datasets. The first one compiled all the interactions occurred during the problem solving task. Here the keyboard indicators were filtered out from the dataset since the focus was put on evaluating the correlation between mouse interaction and the participants' affective states reported using the SAM scale. The second dataset consisted of all the information from participants' emotional reports, so the mouse interaction data was filtered out in order to focus the evaluation on the correlation between keyboard usage and affective states, which were also reported using the SAM scale.

To get the affective labeling of these datasets, we grouped all the affective scores provided by each participant in each of the tasks (i.e., the SAM values for valence and arousal) and computed their corresponding mean. To make sure the mean was representative of the experienced affective state by the participant, we filtered out those cases where the standard deviation of the given scores was higher than one (a ten percentage of the highest rating value) either in valence or arousal dimensions.

5. Results

Once the dataset were preprocessed and prepared, we looked for correlations between the computed indicators and the participants' emotional reporting using the SAM scores. From the 138 correlations computed (96 with mouse indicators and 42 with keyboard indicators), we found the following interesting correlations.

5.1. Mouse indicators correlations

First of all, it should be commented that no right button press events were registered, so all the indicators regarding that interaction became useless in our study. This also means that all the processing of the combined button events (left button events + right button events) result in the same values than only the left button processing. Higher correlations were found in valence. In particular, the highest values of correlation found between the features extracted and the valence were: i) the mean time between two consecutive button press events (0.5646), ii) the mean time between two consecutive button release events (0.5546), iii) the standard deviation of the difference between the covered and the Euclidean distance between two consecutive button press events (0.5528), iv) the standard deviation of the difference between the covered and the Euclidean distance between a button release and the following button press events (0.5521), and v) the mean time between a release and the following press button event (0.5508). These data suggest that affective valence scores given by the participants are more related to mouse click events than to the mouse movement performed during the task. Regarding the arousal dimension, cursor movement features are more correlated than the click ones, but the correlation values are very low anyway. The following correlations were found with higher value: i) the mean of the difference between the covered and the Euclidean distance between a button release and the following button press events (0.1300), ii) the mean of the difference between the covered and iii) the Euclidean distance between two consecutive button press events (0.1157).

5.2. Keyboard features correlations

Regarding the affective valence for the keyboard features, the highest correlation values are: i) the standard deviation of the time between two key press events (0.6548), ii) the mean duration of the digraph (0.6112), iii) the mean duration between the first key up and the next key down of the digraph (0.6103), iv) the duration between two key press events when grouped in digraphs (0.6096), and v) the mean time between two key press events (0.6025). These data suggest the benefits of using a mixed approach, which consist of an analysis of single keystroke events, digraphs and trigraphs instead of using indicators just from single keystroke events or digraphs and trigraphs (as is commonly done when processing keyboard interactions) as both approaches present highly correlated features. As to the arousal dimension, the following correlations were found (also with lower correlation values than those from the valence): i) number of keys pressed (0.4182), ii) numbers of alphabetical characters pressed (0.4174), iii) the mean of the duration of the second key of the digraphs (0.3966), iv) the duration of the third key of the trigraphs (0.3960), and v) the standard deviation of the duration of the digraph (0.3664).

5.3. Prediction rates

The mouse and keyboard indicators identified in this work have already been used in first experiments carried out to predict positive or negative valence dimension of participants (due to the higher correlations seen in valence) while performing some tasks. In these experiments, several data mining algorithms were used, namely well-known classification ones (C4.5 and Naïve Bayes) as well as more complex meta-learners (Bagging, Random Forest and AdaBoost) [37]. With the data at hand, the algorithm used seems to be an important factor when choosing the data sources to be used for the prediction of the valence of the affective state with respect to the SAM score provided by the participant. In some cases, keyboard indicators provided the best prediction rates (even better than combining keyboard and mouse indicators). However, in most cases, the combination of both data sources was better. Table 2 reports prediction rates.

Table 2. Keyboard and mouse features prediction rates (bolded best results for each algorithm).

Data source	C4.5	Naïve Bayes	Bagging	Random Forest	AdaBoost
Keyboard	**58%**	**57%**	44%	53%	53%
Mouse	45%	52%	41%	57%	55%
Keyboard + Mouse	56%	50%	**52%**	**59%**	**59%**

6. Discussion

From the correlations reported in Section 5 follows that the proposed indicators show higher correlation with the valence dimension of the affective state reported by the participants than with their arousal dimension. Regarding mouse indicators, both duration between events and some movement indicators are similarly correlated with valence while in the case of the arousal, the movement indicators show slightly higher correlations than time between events. Regarding keyboard processing, the event combination indicators proposed in [26] appear frequently in the higher correlations observed. This shows that single key events with digraph and trigraph computed indicators can be used together to identify behavioral changes caused by the different emotions learners are feeling when carrying out educational tasks. However this interesting outcome should be contrasted with further experiments. The low correlations found between mouse or keyboard indicators and arousal dimension should be discussed. In this sense, it can be found in literature two points of view supporting and not supporting arousal prediction from interaction indicators [20, 27].

Another point to take into account is that interaction indicators have a strong dependence on the task being done (for instance, the behavior shown by a user when playing a videogame is not the same than the one shown when using a word processor) [26]. In our case, the indicators were extracted in an experiment where the task was the same for all the participants, but it should be discussed if the indicators generated when dealing with that task are valid to model the user in other tasks. Even the graphical user interface (GUI) design of the programs involved in the experiment could interfere in the values captured when navigating through that GUI, as some factors such as the number of elements shown or the elements layout could affect the indicators. In literature, most works have focused on extracting indicators while undertaking a specific task. However, some works have focused on an everyday use of computer (extracting the active task in every moment) but the combination of interaction indicators with context and tasks ones and the creation of application-based models has not been deeply addressed [26]. However the approach presented in this work aims to study the interactions performed regardless the task being performed and its presentation, thus following an approach which aims at being applicable in any domain, without the need of any further development. To do that, indicators such as the difference between the distance covered and the Euclidean distance between two click events in mouse have been proposed.

Different interesting patterns could be found when using the keyboard for navigating the interface but not when typing. Our approach could be of interest here since there is more data to be analyzed from the interactions of users who use the keyboard not only as an input device but also for navigation purposes (such as blind people when using screen reader software [34]). Going further, capturing and processing the interactions with assistive technologies (e.g., Braille keyboard) require further analysis. Additional interesting data sources to be explored for affect detection, as commented in the literature review, are coming from new interaction interfaces (such as touch screens) and which usually have sensors that provide environmental data (weather, lighting or location) or behavioral data (device shakes, inclination, etc.).

Another point that requires further analysis is the way the affective information is obtained [38]. As explored in [37], several affective labeling approaches can be used. Labeling interactions can be done either by the learner herself (as here) or by psycho-affective experts. Moreover, emotions can be described by using either a dimensional approach (as the one used in this experiment with the SAM scale) or a categorical one (like the model proposed by Plutchik [39]). Therefore, it is important to make the appropriate choice that allows getting the real affective state experienced by learners in a low intrusive way. In this respect, when the learner is involved (as it is expected to be more aware of her own feelings than another person) a related issue is the frequency the learner is asked about her emotions, as asking very frequently could interfere in the ongoing activity (and maybe in the learning process and even in the affective state reporting). Note that the final goal of this research is to use the proposed indicators to detect without the involvement of the user her affective state while carrying out learning tasks and thereof to offer personalized affective recommendations that help her to improve her educational results [40]. In this respect, there are still a lot of issues to tackle, such as the intricate relationship between students' emotions and their feedback on recommendations elicited in order to cater for their feelings. Preliminary analysis carried out in our research suggests that personality traits might have a significant impact on the way recommendations are to be delivered, and even, in the decision on whether to deliver or not a given recommendation [42].

7. Conclusion and Future Work

This paper has described the first analysis that we have carried out on evaluating the correlation between mouse interaction (computing 96 mouse indicators), keyboard usage (computing 42 keyboard indicators) and the participants' affective states reported using the SAM scale. Results from the analysis of data processed from 17 participants suggest that these indicators could be useful in detecting affective states automatically in a non-intrusive and low cost way from changes in their behavior during the interaction with the e-learning platform, but more experiments have to be done to clarify some open issues.

We are designing another experiment with an intelligent tutoring system [41] which would serve to check whether the results obtained so far are the same for different applications. Additionally, the emotional reporting approaches can also be further explored. The combination of the proposed keyboard and mouse processed features with other emotional data sources (e.g., physiological and facial) could offer better detection rates and thus, lead to explore and further identify which combination of data sources is the most valuable for affective state detection in terms of effectiveness, price and intrusiveness. Even other indicators should be extracted to enrich the ones presented in this work, such as information from the task being performed or the GUI design (number of interaction elements, distances between them, usage flow, etc). An intra-subject approach is also a step to take, as extracting long-term keyboard and mouse interaction information from a single subject is of interest to generate a domain independent affective user model that can be use to provide affective personalized support. Here it would be interesting focusing on some aspects not commonly addressed such as the time and amount of information needed to correctly train a precise affective detection approach.

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